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A comprehensive review on wind turbine power curve modeling techniques

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ABSTRACT

The wind turbine power curve shows the relationship between the wind turbine power and hub height wind speed. It essentially captures the wind turbine performance. Hence it plays an important role in condition monitoring and control of wind turbines. Power curves made available by the manufacturers help in estimating the wind energy potential in a candidate site. Accurate models of power curve serve as an important tool in wind power forecasting and aid in wind farm expansion. This paper presents an exhaustive overview on the need for modeling of wind turbine power curves and the different methodologies employed for the same. It also reviews in detail the parametric and non-parametric modeling techniques and critically evaluates them. The areas of further research have also been presented.

Contents

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1. Introduction

The significance of alternate energy sources like solar, wind, biomass etc. has exponentially increased in the recent times due to the ever increasing demand for clean energy. Harvesting of wind energy has hence gathered sufficient momentum in the recent days. Estimation of the technical and economic wind energy potential in various regions have gathered momentum [1]. However, the large scale integration and penetration of wind energy into the power grid can result in significant social, environmental, economical and technical impacts [2]. In order to develop a sustainable power system for the future, these impacts need to investigated and mitigated.

Wind energy definitely holds out a promising respite, but for the uncertainty involved in power produced due to the stochastic nature of wind. A significant penetration of wind in the present day power system can be realized only if accurate and reliable forecasting models are made available. A wind turbine power curve can go a long way in fulfilling this. Fig. 1 shows a wind turbine power curve (WTPC).

The output power of a wind turbine significantly varies with wind speed and hence every wind turbine has a very unique power performance curve. A power curve aids in wind energy prediction without the technical details of the components of the wind turbine generating system [3]. The electrical power output as a function of the hub height wind speed is captured by the power curve. The minimum speed at which the turbine delivers useful power is known as the cut-in speed (u_c). Rated speed (u_r) is the wind speed at which the rated power, which is the maximum output power of the electrical generator, is obtained. The cut-out speed (u_s) is usually limited by engineering design and safety constraints. It is the maximum wind speed at which the turbine is allowed to produce power. Power curves for existing machines, derived using field tests, can be obtained from the wind turbine manufacturers. The approximate shape of the power curve for a given machine can also be estimated using the power characteristics of rotor, generator, gearbox ratio and efficiencies of various components. The conversion of power in the wind into actual power varies non-linearly because of the transfer functions of available generators [4].

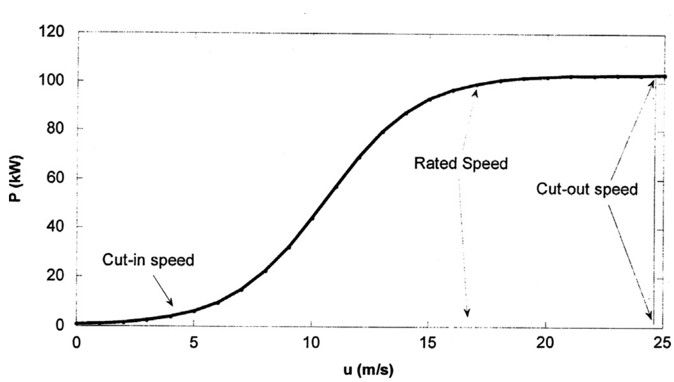

Fig. 1. Typical wind turbine power curve.

The theoretical power captured by the rotor of a wind turbine (P) is given by

$$P = 0.5\rho\pi R^2 C_p u^3 \quad (1)$$

where ρ is the air density, R is the radius of the rotor, C_p is the power coefficient and u is the wind speed [5]. As the air density remains almost constant at hub height, the power captured significantly depends on the power coefficient and wind speed. The power coefficient, which denotes the percentage of power captured by the turbine, essentially depends on the tip speed ratio (λ) and β the blade-pitch angle.

2. IEC power curve

The International Standard IEC 61400-12-1 has been prepared by the International Electrotechnical Commission (IEC) technical committee 88: Wind turbines. The standard methodology for measuring the power performance characteristics of a single wind turbine has been specified here. It is also applicable for testing the performance of wind turbines of varied sizes and types. It can be used to evaluate the performance of specific turbines at specific locations and also aid in comparing the performance of different turbine models or settings [6].

The power performance characteristics of wind turbines are ascertained by the measured power curve and the estimated annual energy production. Simultaneous measurements of wind speed and power output is made at a test site for sufficiently long duration to create a significant database under varying atmospheric conditions. The measured power curve is determined from this database. The annual energy production is calculated, assuming 100% availability, by applying the measured power curve to reference wind speed frequency distributions.

The measured power curve is determined by applying the "method of bins", for the normalized datasets using the following equations:

$$u_i = \frac{1}{N_i}\sum_{j=1}^{N_i} u_{n,i,j} \quad (2)$$

$$P_i = \frac{1}{N_i}\sum_{j=1}^{N_i} P_{n,i,j} \quad (3)$$

where u_i is the normalized and averaged wind speed in bin i, $u_{n,i,j}$ is the normalized wind speed of dataset j in bin i, P_i is the normalized and averaged power output in bin i, $P_{n,i,j}$ is the normalized power output of dataset j in bin i and N_i is the number of 10 min data sets in bin i. The accuracy of WTPC models have improved by using the profile information available using remote sensing instruments [7]. However, it has been stated in [8], that

the IEC-based power curve gives the behavior of the wind turbine with the influence of site turbulence. Though the current site data is rendered with reliable accuracy, the IEC power curve contains the hidden effect of current site turbulence, in such a way that its blind application to other sites is not very correct. The IEC procedure also ignores the fast wind fluctuations through the 10 min averaging and the results in obtaining the behavior of the machine independent of wind fluctuations. Hence the need for modeling site-specific WTPC has gained great significance.

3. Power curve modeling requirement

The manufacturer provided power curve for any turbine gives the relationship between wind speed and power at a particular air density. But this curve is neither site-specific nor does it take into account the wear and tear of the turbine. It was observed that there were notable discrepancies between the small wind turbine manufacturer power curves and the test results carried out at high wind speeds [9]. The WTPC is not an adequate model for estimation of power of variable speed wind turbines as it ignores the dynamic behavior of wind [14]. Hence it is necessary that we model the wind turbine power curve, taking into account all these varying parameters. The main objective of modeling of a wind turbine power curve, the statistical analysis of data that forms the basis of modeling techniques and performance metrics that validates the modeling procedures are discussed in detail in this section.

3.1. Modeling objective

A WTPC built from the measured data in a particular site using better modeling techniques will definitely overcome the drawbacks posed by the manufacturer provided power curve and the IEC power curve. A power curve built from the measured data deviates when some power outputs are negative implying wind turbine is consuming energy due to low wind speed and some power outputs vary even when the wind speed is constant. Hence it is necessary that a power curve is modeled with minimum error. The objective for modeling a WTPC is four fold: wind energy assessment and prediction, choice of wind turbines, monitoring and troubleshooting and finally predictive control and optimization of wind turbine performance (Fig. 2).

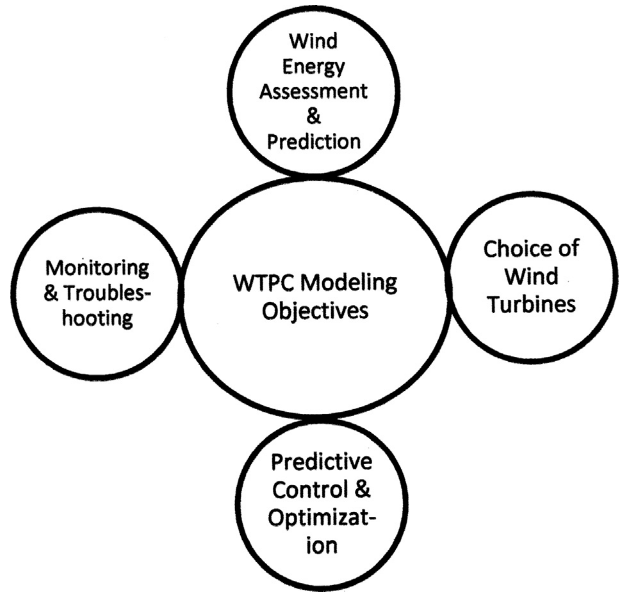

Fig. 2. WTPC modeling objectives.

3.1.1. Wind energy assessment and prediction

Wind resource assessment is the process by which wind farm developers estimate the future energy production of a wind farm. Accurate assessments are crucial to the successful development of wind farms. The meteorological potential of any candidate site is equivalent to the available wind resource [3]. If the wind speed data of the site is available, a WTPC can facilitate the estimation of wind energy that can be produced over a period of time. Accurate WTPC models also help in the planned expansion of wind farms [10]. An analytical method to estimate the output power variation in a wind farm has been devised using dynamic power curves in [11]. Estimating and controlling the variability of wind farm power output aids in providing stable wind power to the utility/grid and improves loss of load expectation (LOLE). Olaofe and Folly have concluded that the analysis of the energy outputs of the wind turbines based on the developed site power curves is more accurate than the turbine power curves [12]. The WTPC models can very well be used for wind power forecasting at varying time horizons [13]. Accurate forecasting of wind power in intra-day and day-ahead electricity markets are the need of the day. The power curve of a variable speed wind turbine has been modified using a new curve called the controllers power curve to account for the wind dynamics and has resulted in more accurate power prediction [14].

3.1.2. Choice of wind turbines

WTPC models aid the wind farm developers to choose the generators of their choice, which would provide optimum efficiency and improved performance. The impact of WTPC on the cost of energy and optimal system configuration in a small wind off-grid power system has been presented in [15]. Judicious choice of a wind turbine generator that yields higher energy at higher capacity factor can be done by using the normalized power curves proposed in [16]. These generalized curves, obtained from a new ranking parameter known as wind turbine performance index, can be used at the planning and development stages of wind power stations. The wind turbine capacity factor was modeled using the site wind speed and turbine power curve parameters in [17,18]. An increase in energy yield up to 5% was obtained, when the proposed model was used for optimum turbine-site matching.

3.1.3. Monitoring and troubleshooting

A WTPC model can serve as a very effective performance monitoring tool [19]. The model developed can be used as a reference for monitoring the performance of wind turbines. An equivalent steady state model of a wind farm under normal operating conditions has been built using data-driven approach and has been utilized for creation of quality control charts, with the aim of detecting anomalous functioning conditions of the wind farms [20]. Monitoring the performance of a wind farm using three different operational curves has been presented in [21]. The WTPC has been used to identify various faults and its severity in [22]. The wind turbine power output has been evaluated and deviations that may result in financial losses are calculated using online monitoring of power curves [23]. The performance of four different data mining approaches has been compared for this purpose.

3.1.4. Predictive control and optimization

Uluyol et al., showed that the WTPC can be very useful for performance assessment and for generation of robust indicators for component diagnostics and prognostics. Higher reliability and lower maintenance costs can be incurred by employing condition-based rather than hour-based monitoring [24]. A copula model

of WTPC has been used for early identification and detection of incipient faults such as blade degradation, yaw and pitch errors [25]. The copula-power curve condition monitoring correlates faults or anomalies to statistical signatures. Kusiak and Li have shown that power curve models along with data mining based model extraction could be used to predict specific faults with an accuracy of 60 min before they occur [22].

3.2. Modeling data

The data required for modeling a power curve is the wind speed and power output recorded at periodic intervals over a long time. The historical data could either be obtained from experimental wind farms or from the Supervisory Control and Data Acquisition (SCADA) system. Once the required data is available, the energy production of the wind turbine can be analyzed using four different approaches namely, direct use of data averaged over a short time interval, the method of bins, development of velocity and power curves from data and statistical analysis using summary measures [3].

3.2.1. Statistical analysis of wind data

The wind speed probability distribution describes the likelihood that certain values of wind speed will occur. The probability distributions are generally characterized by probability density function ($f(u)$) or a cumulative density function ($F(u)$) [3]. The two commonly used probability distributions in wind data analysis are the Rayleigh and Weibull distribution. Rayleigh distribution requires only the knowledge of mean wind speed ($\overline{u}$) and hence is the simplest velocity probability distribution. The $f(u)$ and $F(u)$ of Rayleigh distribution is given below:

$$f(u) = \frac{\pi}{2}\left(\frac{u}{\overline{u}^2}\right)\exp\left[\frac{-\pi}{4}\left(\frac{u}{\overline{u}}\right)^2\right] \tag{4}$$

$$F(u) = 1-\exp\left[\frac{-\pi}{4}\left(\frac{u}{\overline{u}}\right)^2\right] \tag{5}$$

The $f(u)$ and $F(u)$ of Weibull distribution is given in Eqs. (6) and (7).

$$f(u) = \left(\frac{k}{c}\right)\left(\frac{u}{c}\right)^{k-1}\exp\left[-\left(\frac{u}{c}\right)^k\right] \tag{6}$$

$$F(u) = 1-\exp\left[-\left(\frac{u}{c}\right)^k\right] \tag{7}$$

where k is the shape factor and c is the scale factor. Higher the value of k, lesser is the observed wind speed variation. The wind resource of the site under study has been assessed using Weibull's and Rayleigh's distribution in [12].

3.2.2. Factors affecting power curves

Wind farm power curves are adversely affected by the changing environmental and topographical conditions. Equivalent power curve models incorporating the effect of array efficiency, high wind speed cut out, topographic effect, spatial averaging, availability and electrical losses have been built in [26]. The impact of wind speed reduction due to the wakes created by the wind turbines upstream determines the array efficiency. The main factors affecting array efficiency are wind farm layout, wind regime and the type of terrain. Offshore wind farms are susceptible to a higher wake loss. The effect of topography is higher in upland wind farms than the low land wind farms, because of the greater variation in wind speed. This can be reduced by averaging the power from a range of power curves at different wind speeds. An equivalent regional power curve is produced for each wind farm by averaging, in order to reduce the variation of wind speeds experienced by wind farms across a region. Availability and electrical efficiency of offshore sites are generally lower than onshore sites.

The effects of the environmental parameters on wind turbine power probability density function curve were studied in [27]. These parameters included the annual average wind speed, k-factor of Weibull distribution, autocorrelation factor, diurnal pattern strength, altitude above sea level and variance of monthly averaged wind speed in one year. It was found out that the altitude above sea level (which determines the air density indirectly) and the k-factor of Weibull distribution affected the wind turbine output power more than all the remaining parameters.

Site-specific adjustments are required by wind turbine power curves in order to address the effects of turbulence, complex terrain, wind shear, blade fouling and icing, power curve measurement blockage effects and uncertainty in availability of wind farms [28]. It was observed that for a site with 18% turbulence, a 1% reduction of energy took place. Hence for sites, where the predicted turbulence levels and wake effects are more than 15%, a turbulence power curve adjustment factor should be applied. For complex terrains, it was suggested that an up-flow power curve adjustment factor be applied. To account for the uncertainty in power curve and wind turbine availability, an allowance equivalent to 2% of the wind farm energy production has also been suggested. As the output power of wind turbine varies as the cube of the input wind speed, it is the variability in the wind speed that affects the power curve most. If the annual mean wind speed varies by $\pm 10\%$, it was observed that the corresponding variation in available wind energy was about $\pm 25\%$ [29].

3.3. Modeling accuracy

The most important criteria to be addressed while formulating the various techniques for WTPC modeling, is the model accuracy. Different performance metrics have been used by various researchers. The most common metrics have been listed below where P_e is the estimated power and P_a is the actual power and N is the total number of data.

In [5], absolute error (AE) and relative error (RE) are used to evaluate the WTPC models.

$$\mathrm{AE} = |P_e(i) - P_a(i)| \tag{8}$$

$$\mathrm{RE} = \left|\frac{P_e(i) - P_a(i)}{P_a(i)}\right| \times 100\% \tag{9}$$

The use of mean absolute error (MAE), symmetric mean absolute percentage error (sMAPE) and normalized mean absolute percentage error (NMAPE) as performance metrics has been reported in [20].

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|P_e(i) - P_a(i)| \tag{10}$$

$$\mathrm{sMAPE} = \frac{1}{N}\sum_{i=1}^{N}\frac{|P_e(i) - P_a(i)|}{(|P_e(i)| + |P_a(i)|)/2} \times 100 \tag{11}$$

$$\mathrm{NMAPE} = \frac{1}{N}\sum_{i=1}^{N}\frac{|P_e(i) - P_a(i)|}{\max_{i=1}^{N}(P_a(i))} \times 100 \tag{12}$$

The mean absolute error (MAE) and root mean squared error (RMSE) have been used as metrics in [13].

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_e(i) - P_a(i))^2} \tag{13}$$

The coefficient of determination R^2 is used in [30] to ascertain the accuracy of the developed models.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(P_e(i) - P_a(i))^2}{\sum_{i=1}^{N}(P_a(i) - \overline{P}_a(i))^2} \tag{14}$$

where $\overline{P}_a(i)$ is the mean value of actual power.

4. Power curve modeling methodology

A critical analysis of the various methods used for mathematical modeling of wind turbines has been presented in [31]. The two different kinds of models developed by them are models based on fundamental equation of power available in the wind and models based on the concept of power curve of the turbine. It was concluded that models based on the equation of power were very cumbersome. Models based on the power curve of the turbines gave fairly accurate results. The different techniques available in literature for WTPC modeling have been classified into parametric techniques and non-parametric techniques as shown in Fig. 3.

4.1. Parametric techniques

Parametric techniques are based on solving mathematical modeling expressions. The actual wind turbine generator power output (P_a) can be expressed as given below:

$$P_a(u) = \begin{cases} 0 & u < u_c, u > u_s \\ p(u) & u_c \le u \le u_r \\ P_r & u_r \le u \le u_s \end{cases} \tag{15}$$

where u is the wind speed, u_c is the cut-in speed, u_r is the rated speed and u_s is the cut-out speed, $p(u)$ is the linear variable region between the cut-in speed and rated speed and P_r is the rated power.

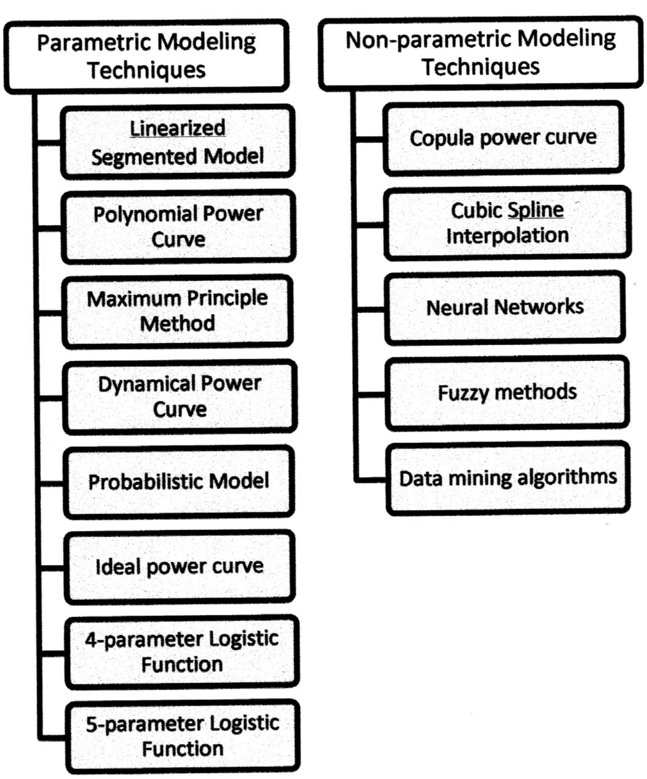

Fig. 3. WTPC modeling techniques.

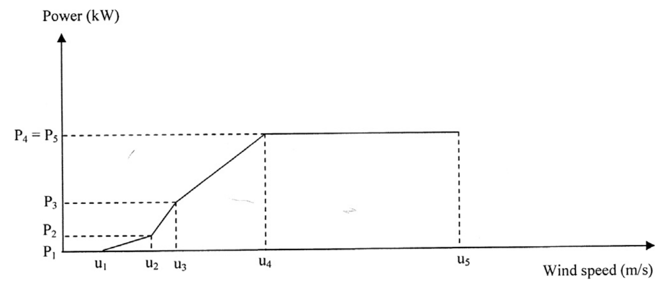

Fig. 4. Linearized segmented model.

4.1.1. Linearized segmented model

This is the simplest parametric model where piecewise approximation of the WTPC has been carried out using the equation of a straight line [13,31,38].

$$P = mu + c \tag{16}$$

where P is the output power and u is the wind speed, m is the slope of the segment and c is any constant (Fig. 4). The data is fitted on to the linear segments using the method of least squares, which estimates the coefficients by minimizing the summed square of residuals. The residual of the ith data point r_i is defined as the difference between the actual power output $P_a(i)$ and the fitted response value $P_e(i)$, and is identified as the error associated with the data. The summed square of residuals (S) is given by

$$S = \sum_{i=1}^{N} r_i^2 = \sum_{i=1}^{N} (P_a(i) - P_e(i))^2 \tag{17}$$

The least squares criterion assumes that the wind measures or forecasts are error-free, which is never true in practice. This problem could be overcome by using the total least square (TLS) criterion, in which the contribution of the noise components in both power and meteorological variables are accounted for in the model parameter estimation [32].

4.1.2. Polynomial power curve

A WTPC has been modeled using polynomial expressions of varied orders in different literatures [33]. Seven different models were used to model the linear region of the wind turbine power curve in [34] and their energy output yields were calculated. A review of four commonly used equations for representation of power curves of variable speed wind turbines namely polynomial power curve, exponential power curve, cubic power curve and approximate cubic power curve has been done in [30]. All these four equations have been used to model the linear region of the WTPC.

1. Quadratic power curve

   A second degree polynomial expression has been used for modeling the WTPC in [30].

   $$p(u) = c_1 + c_2 u + c_3 u^2 \tag{18}$$

   where c_1, c_2 and c_3 are constants determined from u_c, u_s and P_r. A WTPC based on the method of least squares, using quadratic expressions for the linear region has been presented in [31]. Three different quadratic expressions have been used to approximate the linear region guaranteeing better accuracy.

   $$p(u) = \begin{cases} c_{11}u^2 + c_{12}u + c_{13} & for \quad u_c \le u \le u_1 \\ c_{21}u^2 + c_{22}u + c_{23} & for \quad u_1 \le u \le u_2 \\ c_{31}u^2 + c_{32}u + c_{33} & for \quad u_2 \le u \le u_s \end{cases} \tag{19}$$

where c_{11}, c_{12}, c_{13}, c_{21}, c_{22}, c_{23}, c_{31}, c_{32}, c_{33} are coefficients of the quadratic equation and u_1 and u_2 and wind speeds at heights h_1 (m) and h_2 (m) respectively.

2. Cubic power curve
A WTPC has been modeled using a cubic power expression in [30].

$$p(u) = \frac{1}{2}\rho A C_{p,eq} u^3 \tag{20}$$

where $C_{p,eq}$ is a constant equivalent to the power coefficient.
Model for WTPC based on cubic law has also been presented in [31]. Since the fraction of the wind power that gets converted to electrical power depends on several parameters like wind speed, rotational speed of the turbine, angle of attack, pitch angle, mechanical and electrical efficiencies, the accuracy decreases.

3. Approximate cubic power curve
An approximate cubic power curve model has been derived by assigning maximum value to the power coefficient ($C_{p,max}$) in [30].

$$p(u) = \frac{1}{2}\rho A C_{p,\max} u^3 \tag{21}$$

4. Exponential power curve
The variable speed WTPC can be modeled using an exponential equation as given below [30]:

$$p(u) = \frac{1}{2}\rho A K_p (u^\beta - u_c^\beta) \tag{22}$$

where K_p and β are constants.

5. Ninth degree polynomial
The performance of polynomial models of fourth degree, seventh degree and ninth degree has been compared using curve fitting toolbox of MATLAB in [39]. It was observed that the ninth degree polynomial (Eq. 23) performed best.

$$P_a(u) = c_1 u^9 + c_2 u^8 + c_3 u^7 + c_4 u^6 + c_5 u^5 + c_6 u^4 + c_7 u^3 + c_8 u^2 + c_9 u + c_{10} \tag{23}$$

where $c_1,\ldots,c_{10}$ are constants.
The shapes of the WTPC of different turbines with varied design ratings are different. Hence, the biggest disadvantage of the polynomial models is that there can never be a unique set of generalized characteristic equations that can be used for all types of turbines.

6. Model based on Weibull's parameters
A WTPC based on Weibull's parameters has been used in [31] but the accuracy of modeling was very poor.

$$p(u) = a + bu^k \tag{24}$$

where $a = P_r u_c^k / u_c^k - u_r^k$ and $b = P_r / u_r^k - u_c^k$

It was observed that the model based on Weibull's parameters lacked accuracy in the range of cut-in to rated speed since Eq. (24) did not accurately represent the wind turbine power curve shape in that range [31].

Among the polynomial based power curves, the quadratic power curve showed the worst results due to its sensitivity to the data given by the manufacturer and the approximate cubic power curve recorded a better performance [30]. However a polynomial of higher degree recorded better performance in [39].

4.1.3. Maximum principle method

The maximum principle method proposed by Rauh defines an empirical power curve using a very simple method [35]. The power curve is defined by the location, where, in a given wind speed bin, the maximal density of points P_i is found i.e. the power curve is given by the points $\{u_j, P_{k(j)}\}$, where j is the number of the speed bin and $k(j)$ denotes the power bin with

$$N_k := \sum_i \Theta(P_i) - P_k)\Theta(u_i - u_j)$$

and

$$N_{k(j)} \geq N_k \tag{25}$$

where $\Theta(x)$ is a Heaviside function defined by

$$\Theta(x) = \begin{cases} 1 & if -\Delta/2 \leq x < \Delta/2 \text{ with the particular bin width } \Delta \\ 0 & \text{else} \end{cases} \tag{26}$$

However, it was proved that Rauh's method of maximum principle overestimated the points in the region of transition to the rated power in the WTPC and the accuracy of the method was also not good [35].

4.1.4. Dynamical power curve

Determination of WTPC through a dynamical approach has been presented using the Langevin Model in [35]. The main objective of this method is to separate the dynamics of the wind turbine power output into two parts: a deterministic and a stochastic part. The deterministic part corresponds to the actual behavior of the wind turbine and the stochastic part corresponds to other external factors such as the wind turbulence. The wind turbine power output is described as a stochastic process that satisfies the Markovian property and hence can be separated into a drift and a diffusion part.

$$P(t) = P_{stat}(u) + p(t) \tag{27}$$

where $P(t)$ is the time series power data, P_{stat} is the stationary power value dependent on the wind speed u and $p(t)$ corresponds to short-time fluctuations around this value caused by wind turbulence. The performance of the dynamical power curve was compared with the IEC power curve and the maximum principle method according to Rauh and was found to be much accurate.

The advantages of the dynamical power are that it could extract the dynamical behaviour of any wind turbine with better accuracy and produce machine-specific and site-independent results. Measurements taken for a short-time is enough for this approach, where as the IEC power curve procedure requires long-term data and also averages out all the dynamics [36].

4.1.5. Probabilistic model

A WTPC modeled using polynomial expressions is deterministic in nature, since the relationship with the output power and the input wind speed is pronounced by the modeling expressions. Jin and Tian [11] proposed a probabilistic model for WTPC as follows:

$$p(u) = C_p u^3 + \varepsilon \tag{28}$$

In this model, the wind turbine output power is a random number whose value is determined by u, the wind speed and ε, the variation of the power output. This model characterizes the dynamics of wind energy production and estimates the uncertainty in wind power when the wind turbine generators operate in the region between cut-in and rated wind speed. The wind turbine power is assumed to follow the normal distribution with a varying mean and constant standard deviation.

4.1.6. Ideal power curve

The ideal power curve, as proposed in [8], describes the intrinsic performance of the turbine, eliminating the hidden effect of the site turbulence. The ideal power curve refers to ideal conditions such as steady and laminar flow of wind, absence of yaw error and steady state power output. Assessment of wind energy available in a test

site and extension of power curve to sites with different turbulence levels are the main applications of the ideal power curve. It is analytically derived by a Taylor's expansion and uses an accurate assumption of the ideal power coefficient. The convergence of the Taylor's expansion has been improved by applying the Shanks' transformation. The proposed ideal power curve was successfully compared with the IEC power curve. The calculation of annual energy estimated using the ideal power curve was well within the inherent experimental error.

4.1.7. Four parameter logistic function

The shape of the power curve is similar to the four parameter logistic function and hence WTPC models have been built based on this in [5,19].

$$P = a(1+me^{-u/\tau}/1+ne^{-u/\tau}) \tag{29}$$

The vector parameters of the logistic function, a, m, n and τ determine its shape. The parameters of the logistic function have been estimated using the least squares method, maximum likelihood method and evolutionary programming (EP) method in [5]. The parameters have been obtained using genetic algorithms (GA), particle swarm optimization (PSO) and differential evolution (DE) in [13]. Power curve models developed based on these showed more accuracy than several non-parametric techniques like neural networks etc.

4.1.8. Five parameter logistic function

The five parameter logistic function was originally used in biological applications and was first applied in wind turbine power curve modeling in [13].

$$P = d+(a-d)/\left(1+\left(\frac{u}{c}\right)^{b}\right)^{g} \tag{30}$$

Parametric models of WTPC has been developed using five parameter logistic expression and the parameters were solved using GA, EP, PSO and DE [13]. This paper has used the merits offered by the modern nontraditional optimization techniques for modeling of wind turbine power curve. It is indeed a highly complicated process to find solution for parametric expression using traditional techniques of optimization for huge datasets. The application of nontraditional techniques improves the accuracy and is very easy to implement. A review on the current state of the art techniques and the latest research advances in computational optimization methods with application to renewable and sustainable energy technologies has been presented in [40]. A review of application of multi-objective optimization methods using evolutionary algorithms for renewable energy technologies has been presented in [41].

The power curve models developed based on the five parameter logistic equation gave the best results when compared to all other parametric and non-parametric models.

4.2. Non-parametric techniques

Non-parametric techniques are used to solve the following assumption:

$$P = f(u) \tag{31}$$

Several non-parametric methods have been used to find the relationship between the input wind speed data and output power. A brief description of such techniques used to model the WTPC has been given below:

4.2.1. Copula power curve model

Copula is a distribution function in statistics and is used to describe the dependence between random variables. A copula model of wind turbine performance has been developed in [25,37]. This method includes the measures of uncertainty while estimating the performance and also allows comparison of inter-plant performance. A copula representation of a WTPC is constructed by considering the power curve to be a bivariate joint distribution. To make sure that the transformed variables have uniform distribution, accurate estimation of wind speed and power marginals are essential. An estimated power curve copula is shown as a non-parametric probability density estimate in [25]. But this approach can be made fully useful, only if a more advanced method of parametric estimation of marginals and dependency is in place which may take the form of a mixture density estimate of the marginals and cubic spline estimate of the copula. This would aid in capturing and identifying changes in the operating regime also.

4.2.2. Cubic spline interpolation technique

Interpolants and smoothing spline are the non-parametric fitting techniques used to draw a simple, smooth curve through the data [42]. Interpolation is the process of estimating values that lie between two known data points. The different kinds of interpolant methods include linear interpolation, nearest neighbor interpolation, cubic-spline and Piece-wise Cubic Hermite Interpolation (PCHIP). The WTPC model has been approximated using the cubic-spline interpolation technique in [31]. This method fits a different cubic polynomial between each pair of data points. The method of least squares and cubic spline interpolation performed extremely well for wind turbines with smooth power curve.

4.2.3. Neural networks

An artificial neural network (ANN) is an information-processing model simulating the operation of the biological nervous system. It has a significant capacity to derive meaning from complicated or imprecise data and finds application in extraction of patterns and detection of trends that are too complex to be identified by humans [43].

Under normal conditions, the equivalent steady state model of wind farm has been built using three different neural network models namely, generalized mapping regressor (GMR), a feed-forward multi layer perceptron (MLP) and a general regression neural network (GRNN) in [20]. GMR is a novel incremental self-organizing competitive network. NN models like radial basis network and generalized regression network was used for estimation of annual energy in [33]. The WTPC was modeled using a multilayer feed forward back propagation network in [13].

4.2.4. Fuzzy methods

Fuzzy logic is basically a multi-valued logic which deals with approximate reasoning. Fuzzy logic based on Takagi–Sugeno model was used to model the annual wind energy produced in [33]. Modeling of WTPC using fuzzy based methods includes fuzzy cluster center method, fuzzy *c*-means clustering and subtractive clustering.

(1) Fuzzy cluster center method
Ustunas and Sahin proposed the application of fuzzy model based on cluster center estimation to WTPC modeling [44]. The wind turbine power generation data are clustered and the cluster centers are determined using the model algorithm. The more the number of clusters, higher is the accuracy of the technique. The performance of the fuzzy cluster center method is better than the least squares method.

(2) Fuzzy *c*-means clustering
A WTPC model has been done using fuzzy *c*-means (FCM) clustering algorithm in [39]. Unlike *K*-means clustering, FCM

eliminates the effect of hard membership. It employs fuzzy measures as the basis for calculation of membership matrix and identification of cluster centers, permitting data points to have different degrees of membership to each of the clusters [45]. Fuzzy clustering and similarity theory have been applied in [46] to classify the measured wind speed data from different time. A fixed output value is chosen to represent the wind turbine output power in that category. The non-parametric technique FCM, has been used to model the wind turbine power curve in [13] and its performance has been compared with many other models.

(3) Subtractive clustering
Subtractive clustering algorithm has been used for modeling WTPC in [39]. This algorithm is very similar to mountain clustering, but the density function is calculated only at every data point, instead of at every grid point. The number of computations is reduced significantly, since the data points themselves become cluster centers [45].

Among all these three methods, the fuzzy cluster center method gives the best model of the WTPC.

4.2.5. Data mining algorithms

Data mining is all about solving problems and extracting valuable information and patterns by analyzing data present in huge databases. The huge volumes of data stored in the SCADA systems of wind farms present a priceless opportunity for the application of data mining algorithms for wind turbine technology.

Non-parametric models of a WTPC have been obtained using five data mining algorithms namely multi-layer perceptron (MLP), random forest, M5P tree, boosting algorithm and k-nearest neighbor (k-NN) in [5]. Among all these, the k-NN algorithms performed best.

Four data mining algorithms namely bagging, M5P, REP Tree and M5Rules were used for modeling the WTPC in [13].

The different parametric and non-parametric methodologies employed by researchers for modeling of WTPC ultimately aim at capturing the wind turbine performance accurately and thus use for energy prediction, monitoring and predictive control of wind turbine operation.

4.3. Analysis of wind turbine power curve modeling techniques

According to [31], the models based on the basic concept of power available in the wind (Eq. (1)), like the probabilistic model, cubic power law model etc. do not give accurate results. This is because of the fact that the fraction of wind power that is converted to electrical power depends on several other parameters like rotational speed of the turbine, turbine blade parameters like angle of attack, pitch angle and the efficiencies of the mechanical transmission system and generator efficiency. The models based on the shape of the power curve, like the linearized segmented model, model based on Weibull's parameters etc. do not perform best because the performance of the wind turbines with different design parameters and ratings cannot be modeled using a single set of general equations [31].

It has also been stated in [31] that modeling methods in which characteristic equations are developed based on the actual power curve of the wind turbine is the best. This could be helpful while using the wind turbine power curve model for wind resource estimation and for identifying potential wind farm sites. This will also aid the wind farm owners to make the right choice of turbines. But in an established wind farm, where turbines of different types are installed, this would be impossible. Wind turbines of the same type and make may also output different power for the same wind speed due to several reasons [11]. Moreover, the manufacturer power curve is unavoidably affected by the site turbulence [8]. In established wind farms, there is a significant need for monitoring and troubleshooting, predictive control and optimized operation of the wind turbines. This can be realized only if the power curve is modeled based on the historic wind speed—power data of a wind turbine or a wind farm using suitable curve-fitting techniques. The huge amount of data available from the wind farm gives a sizeable number of training and testing data. Non-parametric techniques based on data mining techniques and neural networks perform well but the parametric techniques involving four and five parameter logistic expressions, whose parameters are solved by DE give the best results [13]. The performance of the wind turbine power curve modeled using five parameter logistic expression, with the parameters optimized using DE has been reported to outperform the linearized segmented model and the models based on neural network, fuzzy logic and data mining algorithms.

5. Inferences and future scope

The manufacturer power curve and the IEC power curve are invariably affected by the site turbulence. Hence it is essential that accurate models are developed incorporating all the possible factors that affect energy conversion in a wind turbine generating system. Further research on using WTPC models should enable them to be used not only for online monitoring but also for identifying links between interrelated anomalies as well as correlation between them. The application of copula–power curve model can also be improved by using sophisticated method of parametric estimation of marginals and piecewise application of copula models [25]. Accurate estimation and control of the variability in the wind turbine output power can greatly aid utility companies in establishing good distributed generation systems and for deploying smart grid systems. Models with reduced error can pave way for efficient control, monitoring and optimization of wind farms.

Since the high wind speed sites are almost full, identification, assessment and development of low wind speed sites is the need of the hour. Wind turbine power curve models will be of great use in this regard. Research and development of wind turbines that have a very low cut-in speed and that which will reach rated power at a lower wind speed is required. The rated power of the wind turbine is reached at approximately 13 m/s in all wind farm classification types at present, but it is more likely to have rated wind speed for onshore turbines by 2030 as 12 m/s or lesser [26]. The big increase in wind energy potential for increasing hub height of wind turbines has greatly encouraged the manufacture and placement of tall turbines as high as 80 m or above.

Developing site-specific WTPC models for offshore sites is one of the biggest challenges in wind industry. This will enable wind resource assessment in these sites, aid in wind farm power forecasting and also facilitate online monitoring and maintenance of wind turbines.

Better facilities of calibration, instrumentation and measurement can also help build accurate models. Availability of historical datasets for various sites can also be of much help in this research.

6. Conclusion

This paper presents a comprehensive overview on the wind turbine power curve modeling techniques. The drawbacks posed by the standard IEC power curve approach and the manufacturer provided power curve lay down the necessity for power curve modeling. WTPC models assist the customers in making the appropriate choice of wind turbines, aid in wind energy assessment and prediction, and revolutionize wind turbine performance monitoring, troubleshooting and predictive control. The various parametric and

non-parametric modeling techniques that have been employed for WTPC modeling have been presented in detail. The performance metrics that measures the accuracy of the models have also been included. The future areas of research, if properly addressed will definitely be a major stride in making the stochastic wind resource into a reliable source of energy, thus transforming the wind farm into a wind power plant.

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